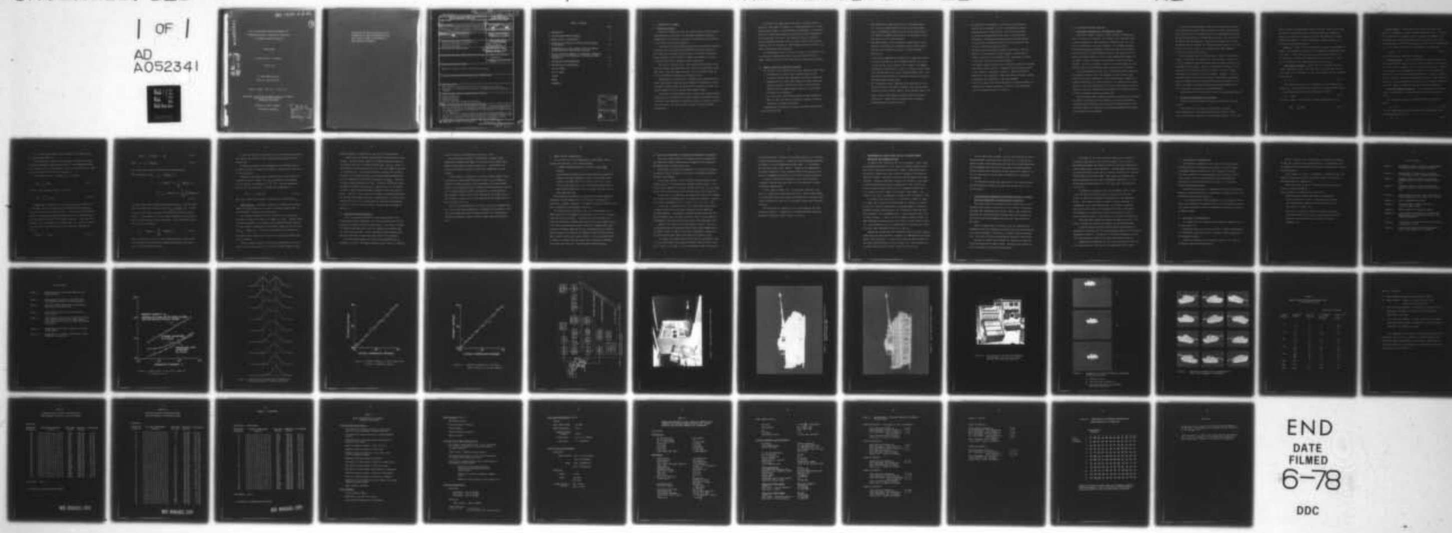
AD-A052 341 CASE WESTERN RESERVE UNIV CLEVELAND OHIO DEPT OF ELE--ETC F/G 6/4
THE USE OF DISTRIBUTED ASSOCIATIVE MEMORIES FOR SURMOUNTING PRO--ETC(U)
MAR 78 Y PAO, W L SCHULTZ DAAG29-76-G-0064

UNCLASSIFIED ARO-13501.3-A-EL NL

| OF |

AD
A052341



END
DATE
FILMED
6-78
DDC

ARO 13501.3-A-EL

9

USE OF DISTRIBUTED ASSOCIATIVE MEMORIES FOR
SURMOUNTING PROBLEMS OF SCALING AND ORIENTATION
IN AUTOMATED PATTERN RECOGNITION

FINAL REPORT

YOH-HAN PAO AND W. L. SCHULTZ

10 MARCH 1978

U.S. ARMY RESEARCH OFFICE
GRANT NO. DAAG29-76G-0064

PERIOD OF GRANT: 1 NOV. 1975 - 31 OCT. 1977

DEPARTMENT OF ELECTRICAL ENGINEERING AND APPLIED PHYSICS
CASE WESTERN RESERVE UNIVERSITY
CLEVELAND, OHIO 44106

APPROVED FOR PUBLIC RELEASE:
DISTRIBUTION UNLIMITED

THE FINDINGS IN THIS REPORT ARE NOT TO BE CONSTRUED AS AN OFFICIAL DEPARTMENT OF THE ARMY POSITION, UNLESS SO DESIGNATED BY OTHER AUTHORIZED DOCUMENTS.

18 ARO 19 13501.3-A-EL

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER

2. GOVT ACCESSION NO.

3. RECIPIENT'S CATALOG NUMBER

4. TITLE (and Subtitle) 6

The Use of Distributed Associative Memories for Surmounting Problems of Scaling and Orientation in Automated Pattern Recognition.

5. TYPE OF REPORT & PERIOD COVERED 9

Final Rep[redacted]t.

1 Nov [redacted] 75 - 31 Oct [redacted] 77

6. PERFORMING ORG. REPORT NUMBER

7. AUTHOR(s) 10

Yoh-Han/Pao [redacted] W. L./Schultz

8. CONTRACT OR GRANT NUMBER(s)

15 Grant DAAG29-76-G-0064

9. PERFORMING ORGANIZATION NAME AND ADDRESS

Electrical Engineering & Applied Physics

Case Western Reserve University

Cleveland, Ohio 44106

10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS

12 52p.

11. CONTROLLING OFFICE NAME AND ADDRESS

12. REPORT DATE

11 10 mar 78

13. NUMBER OF PAGES

14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)

15. SECURITY CLASS. (of this report)

Unclassified

15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

The findings in this report are not to be construed as an official Department of the Army position, unless so designated by other authorized documents.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Pattern Recognition
Automated Tracking
Associative Memory
Position, Scale and Orientation Invariance

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The area of research to which this study relates is that of pattern recognition and in particular, the automated recognition of objects irrespective of the location, orientation and magnitude of such objects in the field of view of the observer.

It is shown that a recently developed Associative Memory technique is suitable for use in a hierarchial mode together with an automated computer video system, for detecting, tracking and subsequently recognizing an object irrespective of variations in location, size and orientation.

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

404 668

TABLE OF CONTENTS

1. INTRODUCTION AND SUMMARY

1.1 Objectives of Study

The area of research to which this study relates is that of pattern recognition and in particular, the automated recognition of objects irrespective of the location, orientation and magnitude of such objects in the field of view of the "observer".

A new type of Associative Memory (AM) had been proposed and explored previously by the principal investigator[1,2] and the overall objective of this study was to determine the feasibility of using this Associative Memory Technique in this context to surmount the problems of location, orientation and scale in automated pattern recognition.

One specific objective was to study certain characteristics of the Associative Memory technique which are of particular importance to this application, including, memory capacity, use in hierarchial form, and use for interpolative prediction of attribute values.

Another specific objective was to implement the interfacing of CCD and/or conventional Vidicon television cameras with computers in order to provide convenient means for acquisition of patterns for input into computer memory for use in the Associative Memory studies.

Yet another specific objective was to indicate how such Associative Memories might be configured in realistic systems for automated tracking of objects, with capability of coping with changes in position, orientation and relative size of the objects, without the need for human intervention.

In this work, the basic approach has been to consider storing a moderately large number of patterns in a multiplexed manner in a single memory without regard to a certain amount of degradation of information. The aim is to span pattern space sufficiently well albeit coarsely so that "recognition" with one of such memories suffices to place the pattern reasonably accurately within a (large) volume in pattern space. Successive use of a hierarchy of similar memories suffices to define the pattern progressively more accurately.

For this approach to be of practical interest, it is necessary that the technique be demonstrably faster and more economical in use of memory capacity relative to other known pattern recognition techniques.

1.2 Summary of Work Done and Results Obtained

The work done can be classified into three categories, these being:

* Investigations of certain basic characteristics of such Associative Memories when implemented for pattern recognition,
* Implementation of a solid state 100x100 CCD sensor television camera and computer interface and also of a full resolution Vidicon television camera computer interface, both suitable for acquisition of patterns,
* Use of the solid state CCD array camera and the Associative Memory to deal with specific problems of position, scale and orientation in pattern recognition.

Although some interesting work remains to be done, the work done in this study show that:

* Many patterns can indeed be stored in a multiplexed manner in a single Associative Memory so that any incident pattern can be simultaneously compared with all of the stored patterns in a parallel processing manner and can be recognized as being most like one of the stored patterns.
* The maximum number of such training set patterns which can be stored in an overlaid, or multiplexed, manner without causing an error in the recognition process is called the Memory Capacity, N_c.
* If the pattern presented for recognition is restricted to being one of the training set, then the Memory Capacity, N_c, can be a large fraction of the dimension of the memory. For example, for patterns consisting of 64 pixels, 11 patterns can be stored in an overlaid manner and can be recognized without error. Such procedures provide the basis for enormous savings in processing time and computer storage space.
* For circumstances where interpolation and prediction of attributes are required the number of patterns which can be usefully stored is generally smaller than N_c, being typically about $0.75N_c$.
* Memory capacity also depends upon how dissimilar the stored patterns are. Memory Capacity increases with the Hamming Distance between the patterns stored.

* The tendency of such memories to group nearly alike patterns together can be exploited to carry out recognition by successive applications of such memories. The first step might be to assign the detected object into one of a few course categorizations. Successive applications provide finer discrimination and finally conformed recognition as being a specific type of object with detailed characteristics.
* The basic Associative Memory technique is described in Section 2.
* Results of investigations of Memory Capacity are described in Section 3 and the use of such memories for interpolative estimate of attribute values is discussed in Section 4.
* The 100x100 compact CCD image sensor developed and used for providing high speed pictorial input to a computer system for pattern recognition research is described in Section 5, together with brief mention of a full resolution system using regular television cameras, and magnetic disc storage and a time base expander.
* Use of the combined CCD video system and the Associative Memory for recognition of objects regardless of position, scale and orientation is described in detail in Section 6.

2. THE ASSOCIATIVE MEMORY TECHNIQUE

2.1 A Qualitative Discussion of the Underlying Concepts

Consider for example, a simple, highly stylized, two dimensional view of a vehicle in silhouette. For a human, such a depiction would be easily recognized as such regardless of changes in the size, location or orientation of the truck silhouette. An automated recognizer working without human intervention could do the same but would have to work quite hard at the task having to resort to such measures as computing the gradient along the contour and/or computing many moments of the object in order to be able to decide whether a vehicle had been detected. The task is even more difficult if internal details are also important and if several different types of objects are of interest.

An alternate approach to the task of recognizing objects regardless of location, orientation and scale would be to store patterns representing all possible combinations of such variables and to compare any incident pattern with all such possibilities. In general this alternate approach is not practicable because of the very large numbers of patterns required to cover all eventualities and because of the excessive memory capacity requirements and long processing time.

The Associative Memory technique approach to surmounting the problems of location, orientation and scale amounts to adopting the generally discredited latter approach, relying on several characteristics of such Associative Memories to overcome the otherwise unacceptable large memory and processing time requirements.

One of the principal concepts consists of storing several patterns in an overlaid, multiplexed, manner so that all of these stored patterns can be compared with any incident pattern in one simultaneous operation. Not only is there savings in storage space but there is no need to fetch stored patterns for comparision, carrying out the comparison, storing the results and then fetching the subsequent pattern and so on. In this manner, the incident pattern can be compared with larger numbers of patterns in any given time interval.

Another characteristic of such memories is that it is fortunately "fuzzy" in just about the right manner, in two aspects. First of all, it can be arranged so that only objects which are greatly dissimilar are recognized to be different. Thus in a first detection stage, it is not important what the precise nature of the object is but it is merely *recognized* to be present in a certain quadrant. Secondly, it is not important that all locations and sizes and orientations be represented, since the memory allows for interpolation between key patterns. In this manner, the number of patterns representing different combinations of size, orientation and location can become manageable.

Further details of the technique can best be discussed quantitatively.

2.2 Mathematical Formulation of Basic System

The basic Associative Memory technique is described in this subsection.

This subsection also includes a description of notation and of definition of binary vector operations resulting in vectors (vector sum and vector product) or scalars (inner product). First, the pattern vectors and constraints on them are defined. Next the associated references are introduced and the associative memory is constructed. Finally, the recognition technique is defined and compared to template matching (correlation). For this comparison, a memory capacity is defined for the associative memory.

Notation. A vector will be represented by an upper case alphabatical symbol. The components of a vector will be denoted by corresponding lower case letters. These upper case vectors and lower case components may be subscripted. Thus the k^{th} component of the vector $\underline{X}$ is x_k. However, the k^{th} component of the vector $\underline{X}_j$ would be written as x_{jk}.

Binary Vector Operations. Vector sum, vector product, and scalar product definitions follow. The vector sum $\underline{S} = \underline{X} + \underline{Y}$ of two vectors $\underline{X}$ and $\underline{Y}$ ($\underline{S}, \underline{X}, \underline{Y}$ all K dimensional) is the usual operation with the components being given by

$$s_k = x_k = y_k \tag{2.2.1}$$

The vector product $\underline{P} = \underline{X}\ \underline{Y}$ is defined by the rule that the components of P are obtained by simple component by component multiplication of the vector multiplier and multiplicand $\underline{X}$ and $\underline{Y}$, namely

$$p_k = x_k y_k \tag{2.2.2}$$

The scalar product of two vectors is defined conventionally, i.e.,

$$\langle \underline{X}\ \underline{Y} \rangle = \sum_{k=1}^{K} x_k y_k \tag{2.2.3}$$

Pattern Vectors. In this method, the patterns are coded into vectors, the components of which are binary valued, being ± 1. Typically, N such pattern vectors would be stored in an Associative Memory. In K dimensional space, each of the pattern vectors, $\underline{X}_n$ (n=1,...,N), would have K components, with the k^{th} compoonent of the n^{th} vector being denoted x_{nk}. These vectors are all of the same length in the sense that

$$\langle \underline{X}_n \underline{X}_n \rangle = K \tag{2.2.4}$$

and therefore may be considered as normalized.

Reference Vectors. A set of orthonormal basis vectors spanning the M dimensional pattern space is used as reference vectors in the construction of an Associative Memory and in the recognition process. In addition, if this memory is to be implemented in software, it is necessary that there exist a fast discrete transform algorithm with respect to representation in terms of these orthonormal reference vectors. Walsh functions satisfy all these requirements and are often used as reference vectors in this work. Other equivalent sets may also be used as appropriate.

Associative Memory Construction. In this technique, each pattern vector is multiplied by a reference vector and the vector product is stored.

For one pattern $\underline{X}$ and the associated reference $\underline{Y}$ we have the memory

$$\underline{M} = \underline{X}\,\underline{Y} \tag{2.2.5}$$

This one pattern memory has the property that multiplciation of $\underline{M}$ by $\underline{X}$ represents $\underline{Y}$ exactly, i.e.,

$$\underline{X}\,\underline{M} = \underline{Y} \tag{2.2.6}$$

For a single pattern stored, each component of the memory vector M is also binary valued, $\pm$ 1.

In this technique, storage of many patterns is achieved by adding the pattern-reference products cumulatively, so that although the memory $\underline{M}$ of N patterns remains a K component vector, the components are no longer binary valued but may have any value between $\pm$ N.

For N patterns stored, the memory $M_{(N)}$ is given by

$$\underline{M}_{(N)} = \sum_{n=1}^{N} \underline{X}_n \underline{Y}_n \tag{2.2.7}$$

and each of the components of $\underline{M}_{(N)}$ is given by

$$m_k = \sum_{n=1}^{N} x_{n,k} y_{n,k} \tag{2.2.8}$$

Recognition. Recognition of an unknown pattern $\underline{X}_j$ is carried out in two steps. The first step consists of multiplying the memory $\underline{M}_{(N)}$ by $\underline{X}_j$ to form the pattern memory product. In the case of a single stored pattern, the associated reference $\underline{Y}_j$ would have been recovered and this would conssitute recognition of the pattern being $\underline{X}_j$. In the case of N patterns, if $\underline{X}_j$ is a member of the training set, i.e., one of the stored patterns, then the pattern memory will be primarily $\underline{Y}_j$ together with "noise".

For $$\underline{M}_{(N)} = \Sigma \; \underline{X}_n \underline{Y}_n \tag{2.2.9}$$

$$\underline{X}_j \cdot \underline{M}_{(N)} = \sum_n \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \equiv k \, C_k \underline{Y}_k \tag{2.2.10}$$

where $$C_k = \sum_n < \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \underline{Y}_k > \tag{2.2.11}$$

and is obtained by using the Fast Walsh Transform algorithm.

More specifically
$$\begin{aligned}
\underline{X}_j \cdot \underline{M}_{(N)} &= \sum_{n,k} < \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \underline{Y}_k > \underline{Y}_k \\
&= \sum_n < \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \underline{Y}_j > \underline{Y}_j + \sum_{\substack{n,k \\ k \neq j}} < \underline{X}_k \cdot \underline{X}_n \underline{Y}_n \underline{Y}_k > \underline{Y}_k \\
&= \underline{Y}_j + \sum_{n \neq j} < \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \underline{Y}_j > \underline{Y}_j + \sum_{n=1}^{N} \sum_{\substack{k=1 \\ k \neq j}}^{K} < \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \underline{Y}_k > \underline{Y}_k
\end{aligned} \tag{2.2.12}$$

It is seen that in this case the associated reference $\underline{Y}_j$ is not recovered with unit coefficient, the noise term being $\sum_{n \neq j} < \underline{X}_j \cdot \underline{X}_n \underline{X}_n \underline{Y}_j > \underline{Y}_j$. In addition, the coefficients for all the other Walsh functions do not vanish either. In this method, of all the k Walsh functions, we are interested only in those which were used as references. In the third term in equation (2.2.12), for each $\underline{Y}_k$,

$$C_k = < \underline{X}_j \cdot \underline{X}_k > \underline{Y}_k + \sum_{\substack{n=1 \\ n \neq k}}^{N} < \underline{X}_j \cdot \underline{X}_n \underline{Y}_n \underline{Y}_k > \underline{Y}_k \tag{2.2.13}$$

and it is seen that C_k for $n \neq k$ carry information also. The k=n term is in essence the cross correlation between patterns $\underline{X}_n$ and $\underline{X}_j$, while the $k \neq n$ sum represents the noise.

In practice, members of the training set can be recovered exceedingly well and the real utility of this technique goes beyond that straightforward step.

Of greater importance is the performance of the technique when it is used to estimate the values of attributes of patterns other than those of the training set.

Estimation of attribute values constitutes the second step of the recognition process. Namely, if for $\underline{X}_n$, the members of the training set, the value of the attribute $A^{(1)}$ are $A_n^{(1)}$, then the expectation value of $A^{(1)}$ for pattern $\underline{X}_j$ is predicted (or estimated to be)

$$< A^{(1)} >_j = \sum_n f(C_n) A_n^{(1)} \qquad (2.2.14)$$

where $f(C_n)$ denotes some nonlinear functional of the coefficients C_n.

<u>Memory Capacity.</u> The memory capacity N_c is defined as the largest number of patterns which can be stored in the memory without errors in the recognition of members of the training set.

The foregoing discussion indicates that there is no error at all when only one pattern is stored in the memory $M_{(N)}$ (N=1). Further storage of pattern information in the memory in the multiplexed manner peculiar to this technique, degrades the reconstructed reference $\underline{Y}_j$ with the noise term $\sum_{n \neq j} < X_j X_n Y_n Y_j > \underline{Y}_j$. This noise term increases with increasing N, and causes errors intrinsic to this process to occur as the memory capacity is exceeded.

Present incomplete results indicate the N_c depends not only on the dimension of the pattern space but also on the average Hamming distance between patterns, as evaluated over the set of training patterns.

A comparison with template matching pattern recognition gives some insight. For each incident pattern $\underline{X}_j$, template matching requires KN operations to form the N correlation coefficients $<\underline{X}_j \underline{X}_n>$, where k is the dimension of the pattern space and N is the total number of patterns in the training set. The associative memory technique uses $K(1+Log_2K)$ operations, K to multiply $\underline{X}_j$ and $\underline{M}_{(N)}$ and $KLog_2K$ addition/subtractions for fast computation of the Walsh representation of $\underline{X}_j\underline{M}_{(N)}$. Thus when $N<1+Log_2K$, template matching is faster. Conversely, associative memory techniques are faster when $N>1+Log_2K$. However for $N > N_c$, the memory capacity, a single associative memory technique suffers from intrinsic errors. Thus for K = 512, any value of N above 10 represents advantage for the Associative Memory technique. Experimentally it has been determined that for K = 512, N_c can be about 36, representing an advantage of 36 to 10. For K = 64, N_c is about 11 representing an advantage of about 11 to 7.

2.3 Additional Features and Options

One of the principal obstacles to general application of the technique described in subsection 2.2 is the requirement that the components of the pattern vector be binary valued. The state of a system can indeed be represented by an array of numbers but in general they will not be binary valued. So far, preliminary results indicate that there are three ways of coping with this aspect of the technique.

The first method consists of relaxing the requirement that the components be binary. The method does work but the "noise" is generally greater and much of the mathematical niceties is lost.

The second method consists of representing an integer valued component by an appropriate number of +1 values with zero being represented by those spaces all being filled with -1. This method is obviously only suitable for pattern vectors when components are small integers.

A third method is suitable for use with any general pattern vector and consists of representing each decimal digit of a real number as a positive (or negative integer) using the coding of the second method. However in the recognition process, before the Walsh transform is carried out, the pattern-memory product is multiplied by a masking pattern P which assigns a weight of 100 to bits representing the decimal digit in the 100 place, a weight of 10 to bits representing the decimal digit in the 10 position and so on.

Use of this last method results in using 30 bits for representation of a three digit decimal number and is consequently very wasteful. However this seeming expansion in dimensions results in increased multiplexing and consequent savings in memory storage needs and processing time.

3. MEMORY CAPACITY INVESTIGATIONS

For each value of K, the dimensionality of the memory, sets of patterns were generated in the following manner:

* A randomly generated sequence of K bits is used as <u>base</u> pattern.
* Other patterns differing from the base pattern by a specified number of bits are generated by changing the required number of bits, care being taken to see that the entire set of patterns so generated are not only the specified Hamming distance away from the base pattern but are at least that same distance apart from each other.

These patterns are progressively stored in Associative Memory and recognition of these members of the training set is tested until at some stage, a mistake is observed. The number of patterns stored at that stage is defined to be the memory capacity, N_c.

For each value of K, and for any one set of such patterns, the memory capacity can be optimized by appropriate choice of the references associated with the patterns. A generally effective procedure is to choose the references uniformly spaced to scan the entire sequency space. A more precise optimization procedure consists of examining the "power spectrum" in sequency space and varying the references so as to obtain minimum overlap of the spectral contributions from the various patterns. Memory capacity results are listed in Table 3.1 and also shown plotted in Figure 3.1 together with some values which indicate the advantages this method have relative to straightforward template matching.

4. RECOGNITION ACCOMPANIED BY INTERPOLATIVE ESTIMATION OF ATTRIBUTES

This type of memory would be of limited utility if applications were limited to correct identification of members of the training set and happily this is indeed not the case.

The ability to carry out "recognition" in the sense of being able to provide a correct estimate of the value of an attribute was demonstrated in two contexts.

In the first context, a set of patterns each consisting of twelve integer valued ($0 \sim 5$) features were assigned attribute values. This body of data originated in a medical context and in fact it is not known whether the attribute values so assigned are entirely self consistent.

For one set of such patterns, each pattern was coded into a sequence of 41 binary valued components and the sequence was repeated m times to fill a space of dimension K. ($m = 3$ for $K = 128$, $m = 6$ for $K = 256$).

For one set of patterns, for $K = 128$, eight patterns were stored in memory and then used to provide recognition for the remaining available patterns. The patterns, assigned attribute values and estimated attribute values are shown in Table 4.1 and it is seen that the performance is very good, the root mean square error being about 0.6%.

Similarly for another set of such patterns, using $K = 256$, the corresponding patterns, assigned attribute values and estimated values are shown in Table 4.2 and it is seen that performance is again very good with the root mean square error being on the order of 0.5%.

In a sense, these good results are not entirely satisfactory since it is not known whether the assigned attribute values are self consistent. This is to say that it is not known whether there is one metric to the pattern space or whether at the minimum the metric is a function of space distorting perhaps in a smooth and continuous manner depending on position in the multidimensional pattern space. It is suspected that the latter case is more nearly correct and the demonstration of correct recognition is also a demonstration of the ability of this memory to accommodate this feature of the task of pattern recognition.

In another instance, the capability of this type of memory to "recognize" patterns other than those in the training set, is demonstrated more unequivocably.

In this second instance, each of the patterns consisted of two pulses at a specified distance from each other. With a certain number of such patterns stored, the question was whether any new pattern could then be recognized in terms of the interpulse distance being estimated correctly.

The pulses used for formation of one of such memories are shown plotted in Figure 4.1. Comparison of estimated and actual interpulse distances are shown plotted in Figures 4.2 and 4.3.

5. IMPLEMENTATION OF VIDEO SYSTEMS FOR USE IN COMPUTER PATTERN RECOGNITION AND AUTOMATED TRACKING

In support of the theoretical work of this program, a video system was developed consisting of a solid state CCD TV camera (using the Fairchild CCD 202 array with 100x100 sensor elements), camera lens (zoom), pan and tilt servocontrols, level shifters required for CCD operation, television minotors, A/D and D/A converters, digital memory and a CAMAC interface. Although considerable ingenuity was displayed in that aspect of work and although the system so implemented is quite versatile and suited to general pattern recognition and automated tracking work, it is not useful to go into details of that work in this report. Such details can be found in a CWRU Master's Thesis (1977) by Kenneth J. Lauer.

In essence, using that system, it is possible to "snatch" a frame of a scene and to display the snatched frame on a regular T.V. monitor as well as to feed the information to a computer memory for processing. Computer generated tracking signals can be fed back to servos for automated tracking of any recognized object. A block diagram of the system is shown in Figure 5.1 and a view of the system is shown in Figure 5.2. Some performance characteristics of the system are shown listed in Table 5.1. Other demonstrations of the capabilities of the system are provided by printer output exhibited in Figures 5.3 and 5.4.

Another such system using full resolution Vidicon television cameras rather than CCD arrays was also developed in our laboratories with partial support from this project. A view of that system is shown in Figure 5.5 and system specifications are listed in Table 5.2. Further details are available from CWRU Master's Thesis (1978) by John W. Allen.

In this latter case, customary full 512 line resolution is available and storage is achieved using a magnetic disc. A time base expander provides interfacing between the video rates of data acquisition and the somewhat lower rate of data acceptance by computer memories. Higher resolution and multipattern storage capability is gained at the cost of large overall size and greater vulnerability to mechanical disturbances.

The CCD system has been used extensively in this present program and the multipattern magnetic disc/time base expander system is now also available.

6. USE OF ASSOCIATIVE MEMORIES FOR SURMOUNTING PROBLEMS OF LOCATION, SCALE AND ORIENTATION IN AUTOMATED PATTERN RECOGNITION

The results reported in previous sections indicate that the preliminary steps necessary for carrying out the principal investigation had indeed been implemented successfully. Namely, under appropriate conditions the associative memory technique does work satisfactorily and the television sensor/computer/servo pan-tilt zoom system also works well.

Given the capabilities so described, those two components were combined to provide for capability to achieve detection and recognition of an object regardless of variations in location, scale and orientation. The results of that investigation are reported in this section.

Two types of objects were presented for recognition by the television sensor/associative memory system. Recognition was carried out using a hierarchy of three associative memories.

The function of the first Associative Memory was to locate the object and to pan and tilt the television camera so as to center it. The Associative Memory was constructed from nine patterns consisting of a dark square against a light background. The dark squares in each pattern were positioned so that when all nine were overlayed their composite would resemble a tic-tac-toe board. Each pattern was assigned attributes corresponding to its x and y displacement from center, i.e., the center pattern had attributes (0,0), the lower right corner had attributes (8,-8).

To economize on processing time, the information (dark or light) in only one out of every three pixels was retained and the 32x32 picture so obtained was presented for recognition by the Associative Memory. The results presented in Table 6.1 clearly show that in a circumstance such as that described here, this system is capable of detecting the dark object and estimating the location of the object. The performance is estimated to be faster and superior to that of optical contrast trackers. (See Figure 6.1 for a graphic illustration.)

After the servo'd camera had centered the object, the size of the object is determined readily using approach as that described above.

In the third step, the centered and properly ratioed object was presented for recognition by an Associative Memory made up of the patterns exhibited in Figure 6.2. Recognition of the object regardless of orientation was achieved as shown by the results exhibited in Table 6.2.

Feedback and confirmation could have been achieved with the use of a dove prism but this final step was not implemented in this study.

7. CONCLUSIONS AND RECOMMENDATIONS

The experience accumulated in the course of this investigation indicates that the Associative Memory technique is clearly suitable for automated pattern recognition and that problems of location, scale and orientation can be surmounted with this technique. However, it was equally clear that straightforward naive implementations generally were not sufficiently immune to noise or to confusion produced by unexpected objects.

Successful systems need to be implemented with tiers of Associative Memories, including provisions for confirmation, feedback, recovery from misidentification and also adaptivity.

It is recommended that systems capabilities of hierarchical arrangements of such memories be investigated with a view of determining whether such systems are ideally suited for implementing distributed intelligence in complex systems.

8. PUBLICATIONS AND PRESENTATIONS

M.S. theses and Ph.D. dissertation investigations supported in part by this project are:

Kenneth John Lauer, M. S. Thesis, May 1977, "Design and Development of a Solid-State Video System for Use in Computer Pattern Recognition and Automated Tracking".

Jeffrey Lynn Altman, Ph.D. Dissertation, August, 1977, "Pattern Recognition Using Associative Memories".

William L. Schultz, Ph.D. Dissertation, in preparation, scheduled for May 1978, "Characteristics and Applications of Distributed Associative Memory Algorithms (With Emphasis on Pattern Recognition and Automated Image Processing.)"

John W. Allen, M.S. Thesis, in preparation, scheduled for May 1978 "Design and Implementation of a Video Buffer Memory with Time Base Expansion/Compression Capabilities".

During the funding period of the grant, numerous seminars were given by Professor Yoh-Han Pao.

Public lectures by Professor Yoh-Han Pao include:

"Use of Associative Memory Techniques in Implementation of Multivalued Logic Systems", invited paper at the Sixth Annual International Symposium on Multiple-Valued Logic, May 25-28, 1976, Logan, Utah.

"On the Use of Associative Memories for Pattern Recognition and System Control" at the Electric Power Research Institute Parallel Processing Conference, Palo Alto, California, November 1977.

LIST OF FIGURES

LIST OF TABLES

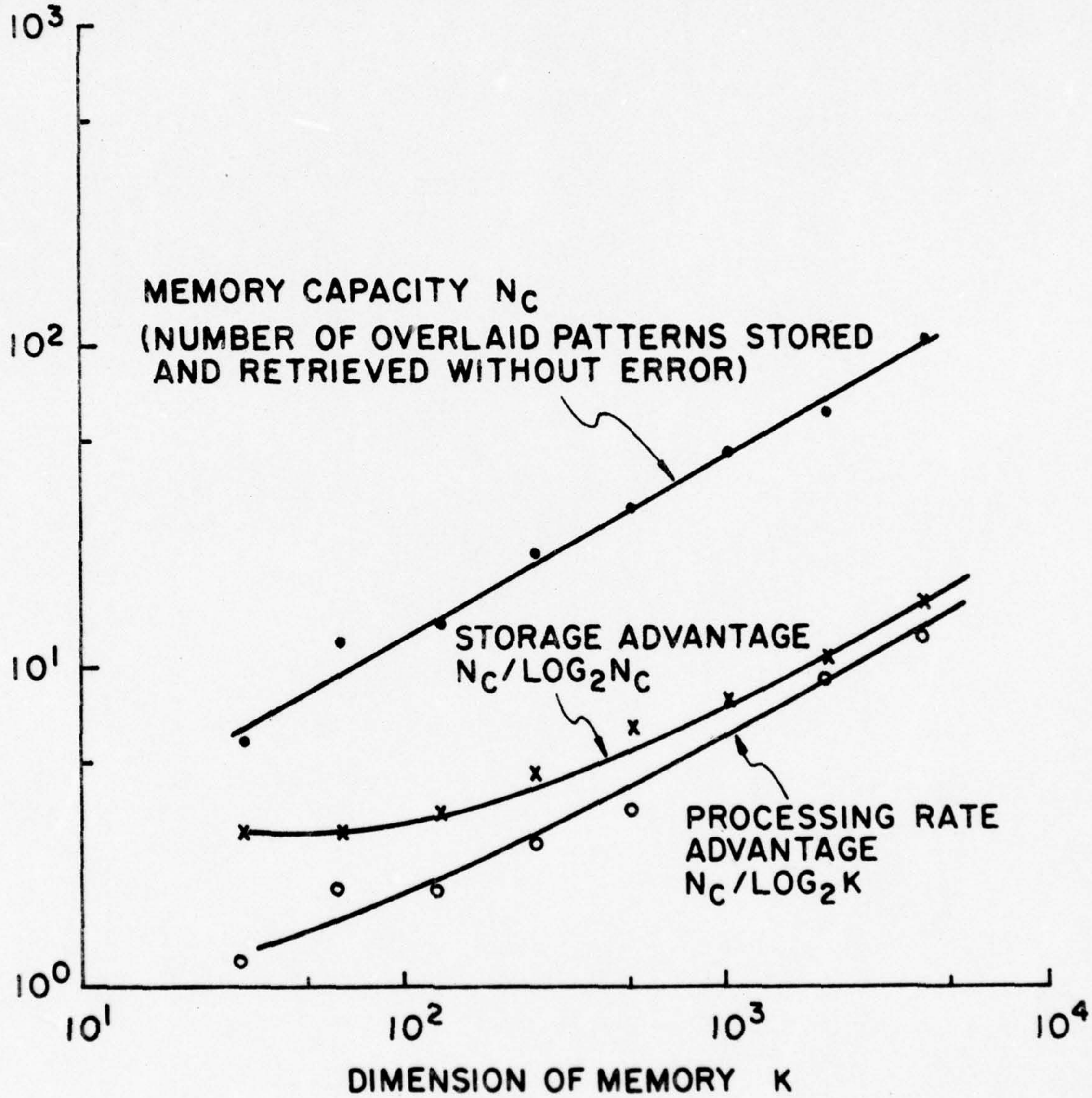


FIGURE 3.1 MEMORY CAPACITY OF ASSOCIATIVE MEMORY AND USE ADVANTAGE RATIOS.

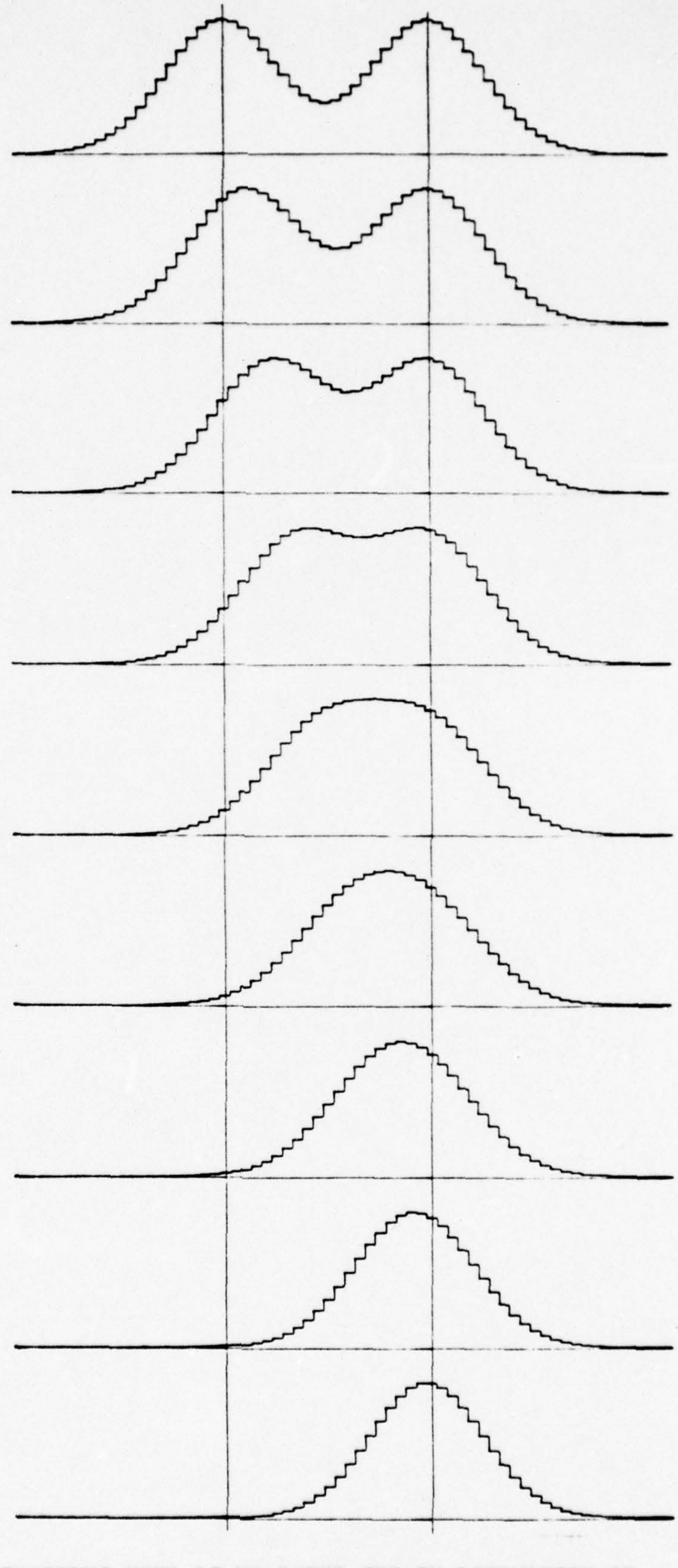


Figure 4.1 PATTERNS USED AS TRAINING SET IN ESTIMATION OF INTERPULSE DISTANCES (9 MEMBER TRAINING SET).

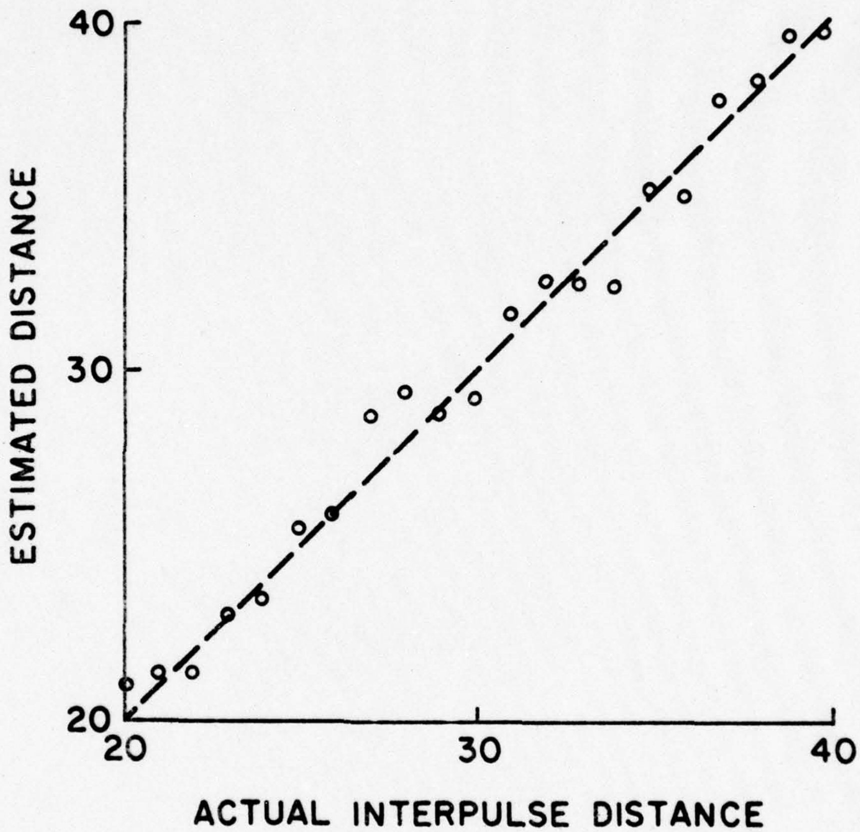


FIGURE 4.2 ESTIMATED INTERPULSE DISTANCE VERSUS ACTUAL DISTANCE (8 PATTERNS IN MEMORY).

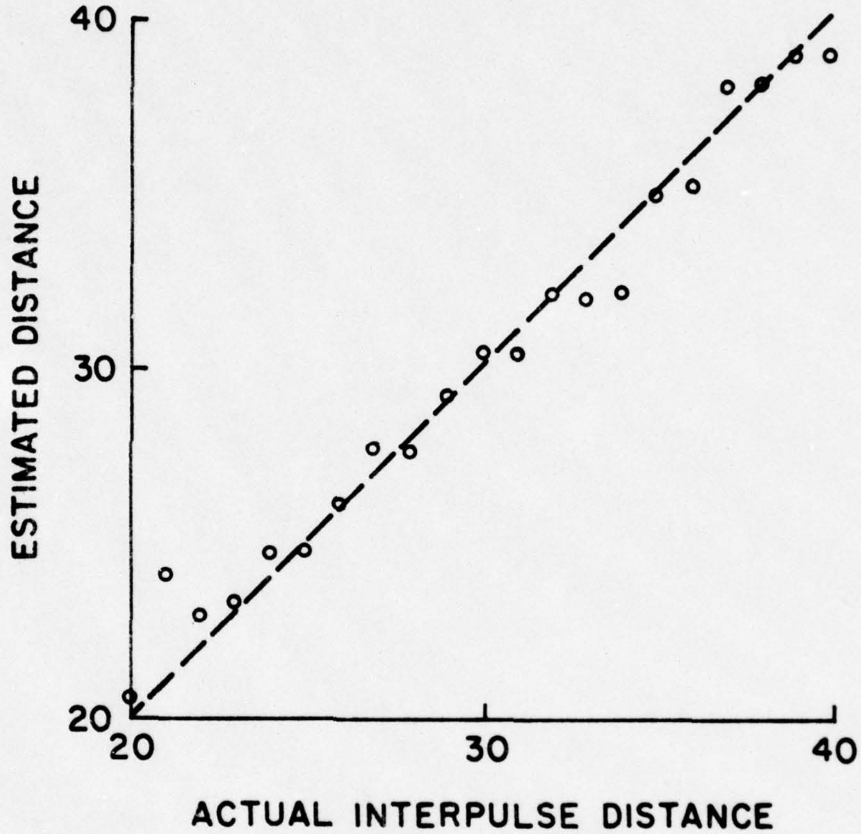


FIGURE 4.3 ESTIMATED INTERPULSE DISTANCE VERSUS ACTUAL DISTANCE (14 PATTERNS IN MEMORY).

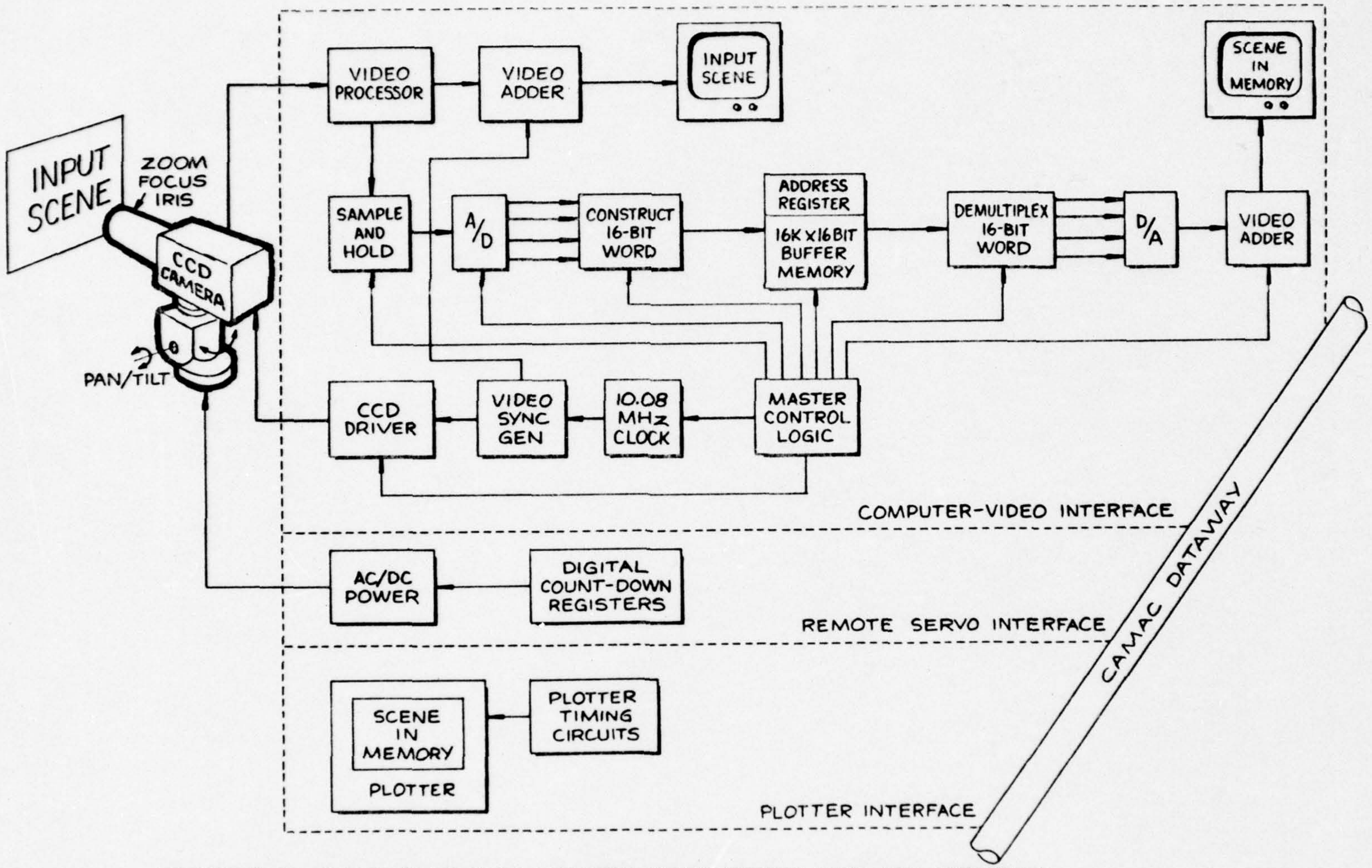


FIGURE 5.1 BLOCK DIAGRAM OF COMPUTER VIDEO SYSTEM USED FOR AUTOMATED RECOGNITION AND TRACKING.

FIGURE 5.2 VIEW OF COMPUTER VIDEO SYSTEM (CCD CAMERA).

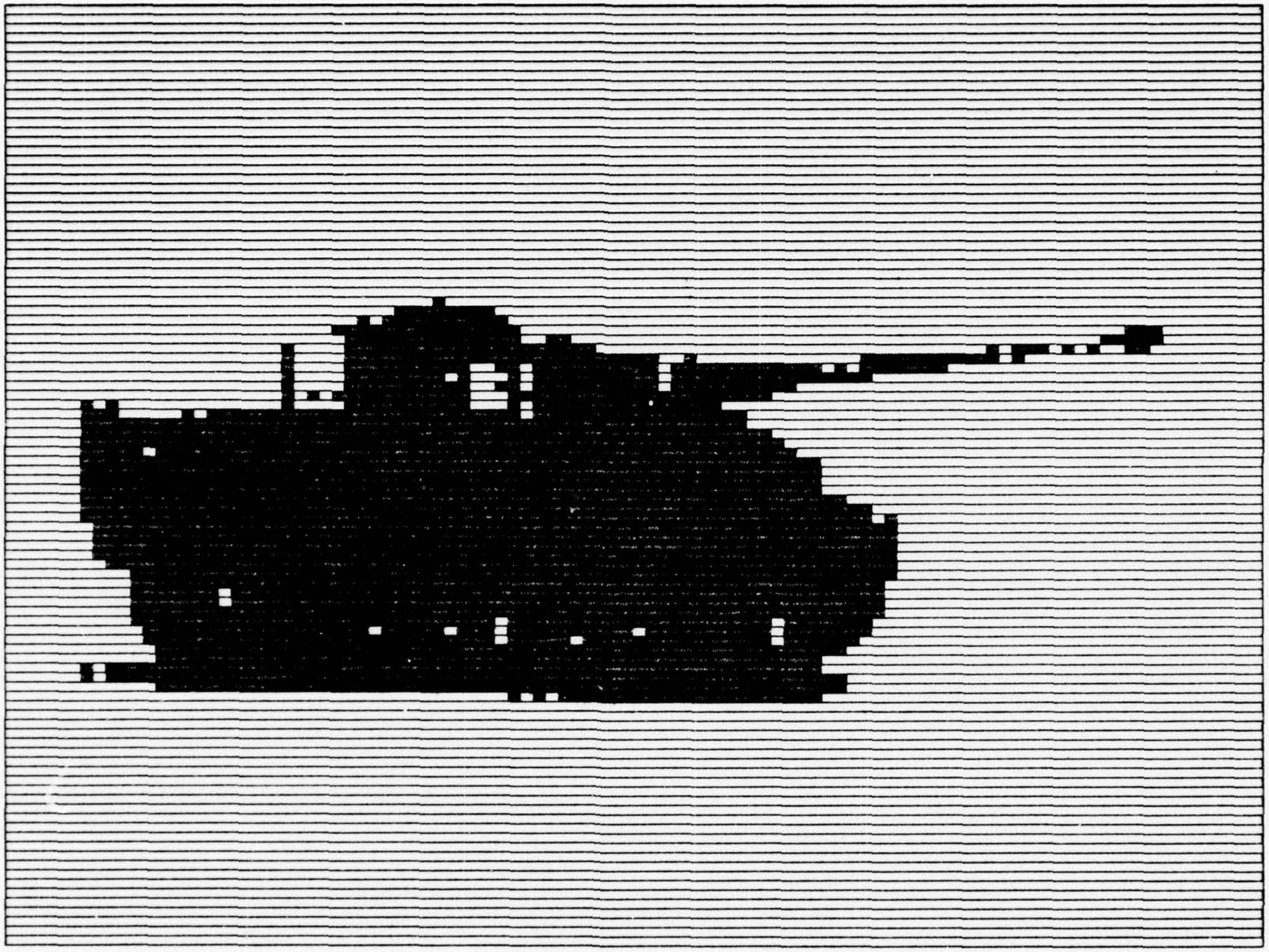


FIGURE 5.3 SILHOUETTE VIEW OF TANK AS ACQUIRED BY A 100x100 CCD ARRAY CAMERA

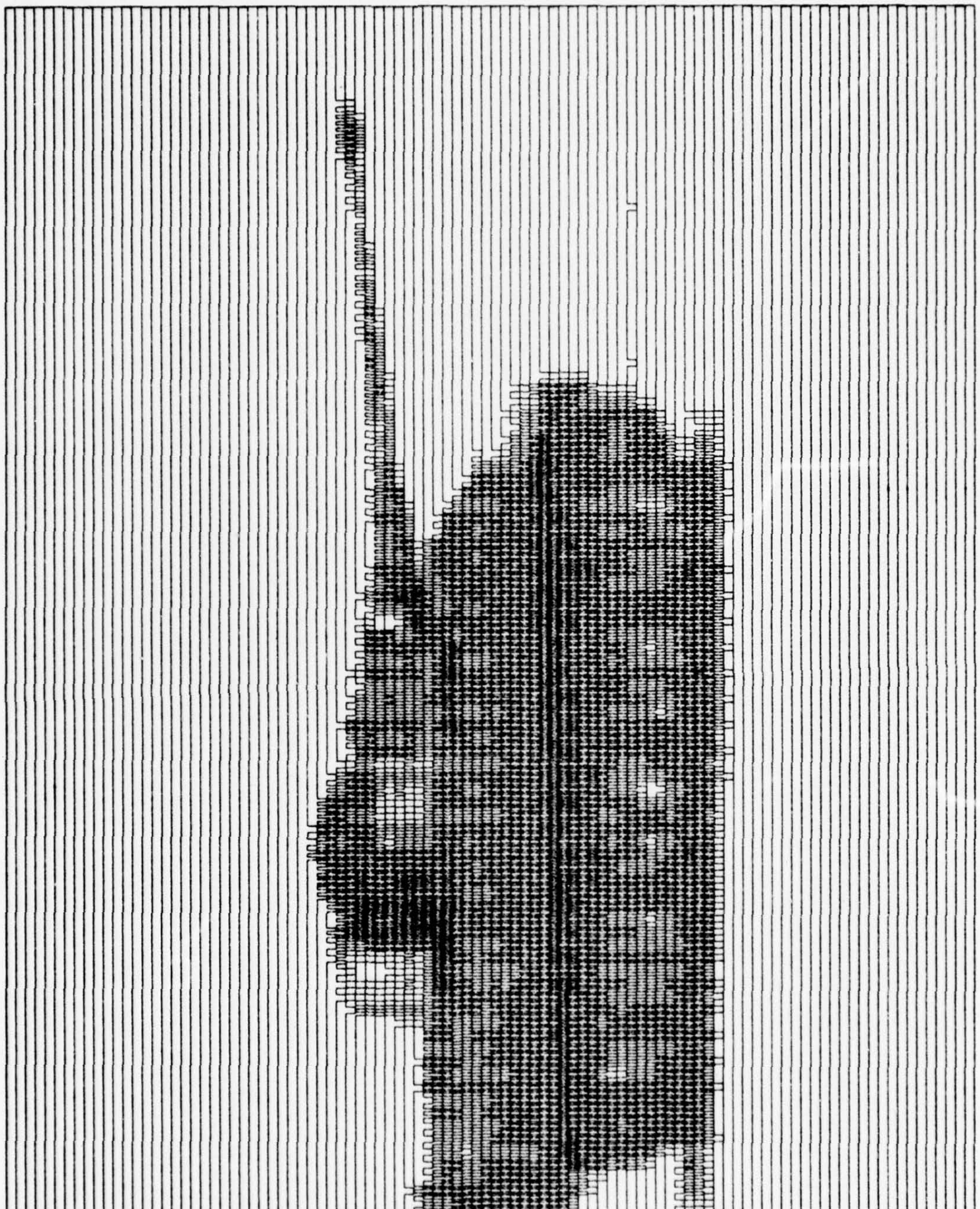


FIGURE 5.4 VIEW OF TANK WITH 16 LEVELS OF SHADING

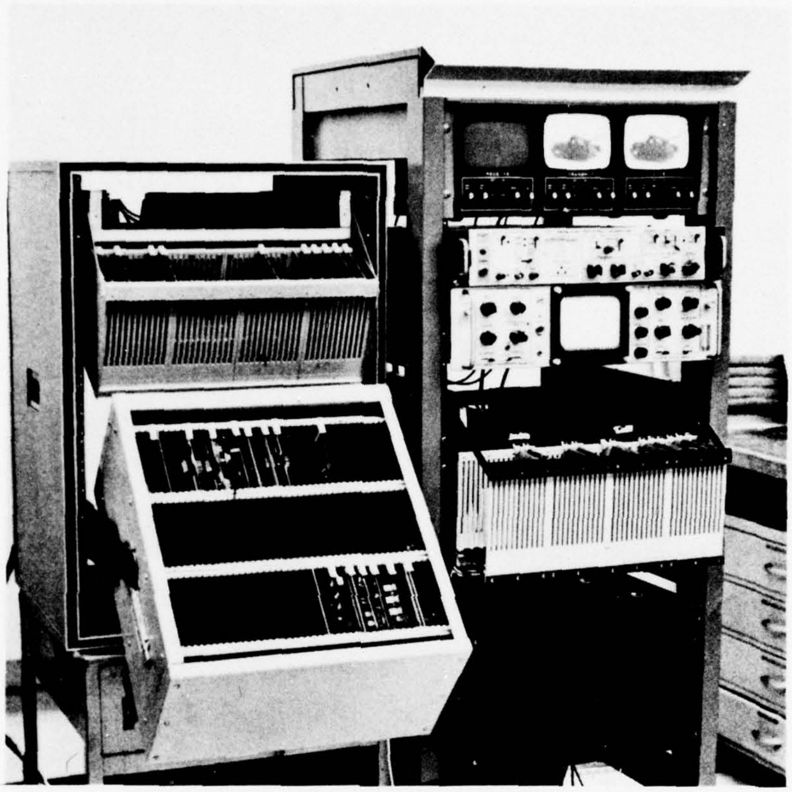
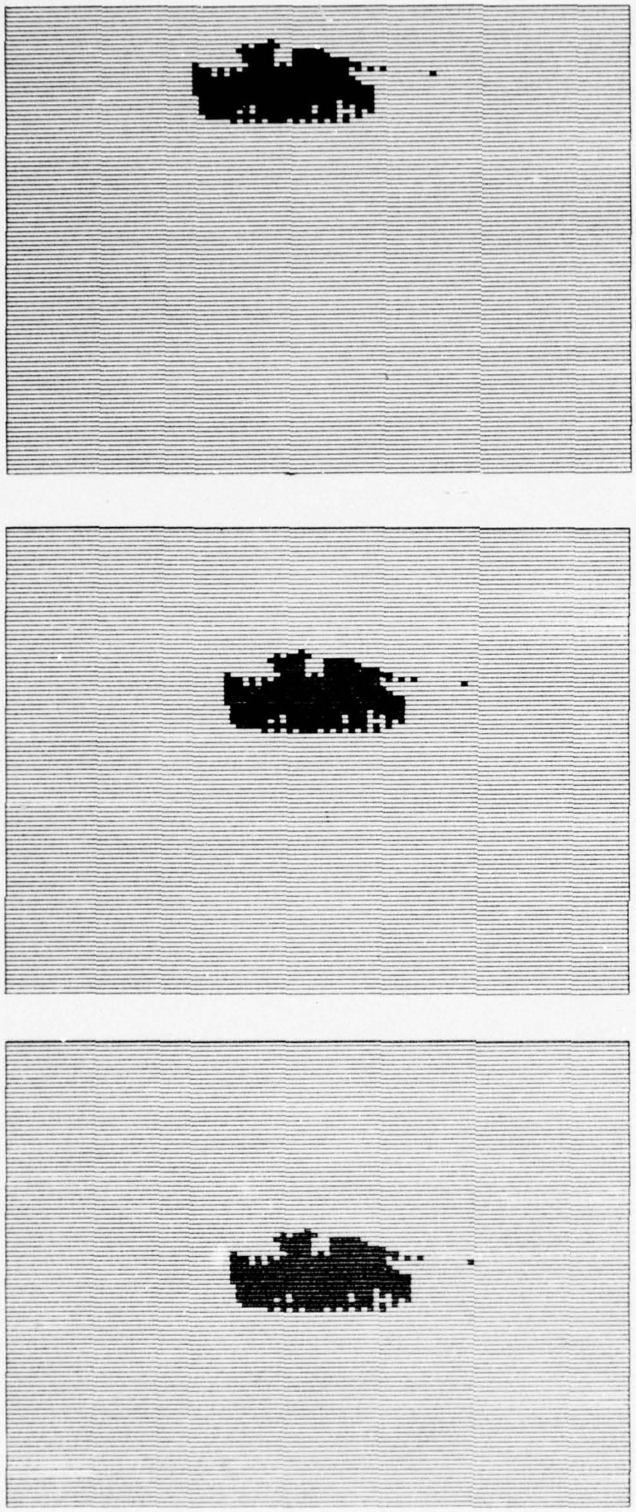


FIGURE 5.5 FULL RESOLUTION COMPUTER VIDEO INTERFACE USING MAGNETIC DISC, ANALOG RECORDING, AND TIME BASE EXPANSION/COMPRESSION.



(a)

(b)

(c)

FIGURE 6.1 ILLUSTRATION OF AUTOMATED TRACKING BY SUCCESSIVE RECOGNITION OF OBJECT

a) Original position

b) After one coarse correction

c) Final position after two additional successive corrections

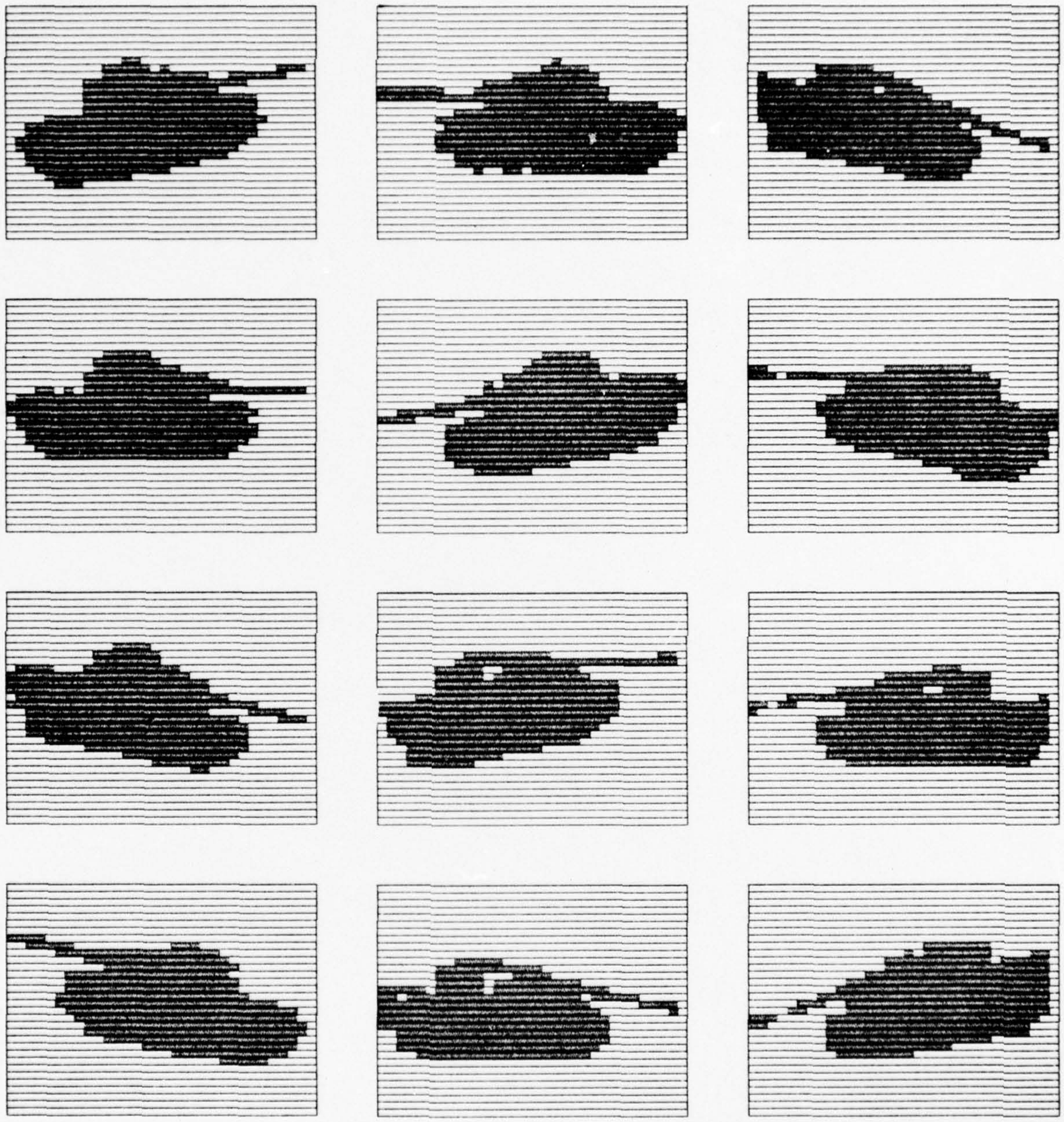


FIGURE 6.2 TRAINING SET PATTERNS USED FOR RECOGNITION OF TYPE OF TANK REGARDLESS OF ORIENTATION.

TABLE 3.1

MEMORY CAPACITY OF ASSOCIATIVE MEMORY AND USE ADVANTAGE RATIOS

Memory Dimension K	Hamming Distance (1)	Memory Capacity N_c (2)	Advantage of Technique: In Storage Requirement $N_c/\text{Log}_2 N_c$ (3)	Advantage of Technique: In Processing Rate $N_c/\text{Log}_2 K$ (4)
32	5	4	2	0.8
	10	4	2	0.8
	15	6	3	1.2
64	10	5	1.6	0.8
	20	9	2.25	1.5
	30	12	3	2
128	20	8	2.6	1.1
	40	12	3	1.7
	60	14	3.5	2.0
256	40	10	2.5	1.2
	80	21	4.2	2.6
	120	23	4.6	2.8
512	80	16	4	1.8
	160	30	6	3.3
	240	32	6.4	3.6
1024	480	47	7.8	7.8
2048	960	64	10.6	9.1
4096	1920	107	15.3	12.6

Table 3.1 Footnotes:

(1) Minimum Hamming Distance Between Patterns in Memory.

(2) Memory Capacity - Number of Overlaid Patterns Stored and Retrieved Without Error.

(3) Storage Capacity Advantage = (Requirement of Template Matching Technique/ Requirement in Associative Memory Technique) = $KN_c/KLog_2N_c = N_c/Log_2N_c$

(4) Processing Rate Advantage ≈ (Number of Operations in Template Matching Technique/ Number of Operations in Associative Memory Technique) = $KN_c/KLog_2N_c = N_c/Log_2K$

This comparison does not take into account the additional advantage due to the fact that N_c patterns are stored <u>in place</u> in the Associative Memory method and N_c "fetch and store" operations are avoided in processing. That advantage is substantially larger than those values listed in Table 3.1.

TABLE 4.1

INTERPOLATIVE ESTIMATION OF ATTRIBUTES USING SOME PATTERNS GENERATED IN A MEDICAL CONTEXT.

CATEGORY 1.

TENTATIVE DIAGNOSIS	PATIENT ASSESSMENT PROFILE	ASSIGNED SEVILL	COMPUTED SEVILL	DIFFERENCE
21	1 2 0 0 0 0 0 0 0 0 0 0	150*	156. 04	-6. 04
21	1 2 0 1 0 0 1 0 0 0 0 0	180	166. 74	13. 26
21	0 2 0 0 0 0 1 0 1 0 0 0	190	153. 25	36. 75
21	1 2 0 0 0 0 1 0 0 0 0 1	180	161. 13	18. 87
21	1 2 0 1 0 0 1 1 0 0 0 1	220	239. 69	-19. 69
21	1 2 0 0 0 0 1 0 1 0 0 0	220	156. 45	63. 55
21	2 2 0 0 0 0 1 0 1 0 1 1	290	242. 82	47. 18
21	2 2 0 0 0 0 0 1 1 0 1 0	290*	307. 38	-17. 38
21	2 2 0 1 2 0 2 0 0 0 0 1	290	367. 13	-77. 13
21	0 2 0 1 0 0 2 1 1 0 0 0	290	277. 43	12. 57
21	2 2 0 0 2 0 1 0 1 0 0 0	290	213. 24	76. 76
21	2 2 0 1 0 0 0 2 1 0 0 0	290	288. 10	1. 90
21	1 2 2 0 1 0 0 1 0 0 0 0	290*	284. 03	5. 97
21	2 2 2 1 0 0 1 0 0 0 0 1	315	317. 33	-2. 33
21	2 2 0 1 2 0 2 1 0 0 1 0	335	407. 30	-72. 30
21	4 0 2 1 0 0 2 0 1 0 0 1	400*	406. 00	-6. 00
21	2 2 0 0 2 0 1 0 5 0 1 0	400	424. 45	-24. 45
21	4 2 2 1 0 0 2 0 0 0 3 0	440	478. 54	-38. 54
21	4 2 0 1 2 0 2 1 2 0 1 0	450*	447. 13	2. 87
21	4 4 0 1 2 0 1 1 1 0 1 0	450*	449. 32	0. 68
21	4 2 0 0 2 4 1 0 1 0 1 0	475	447. 16	27. 84
21	4 2 2 1 0 0 2 0 1 0 0 0	425	418. 52	6. 48
21	4 0 3 0 0 0 1 1 1 0 3 0	500*	499. 17	0. 83
21	4 2 0 1 2 2 2 1 1 0 3 1	475	435. 05	39. 95
21	4 0 3 1 2 0 2 2 1 0 1 0	550*	529. 94	20. 06

RMS ERROR: 35. 26

* INDICATES A TRAINING SET PATTERN

TABLE 4.2

ADDITIONAL RESULTS DEMONSTRATING INTER-POLATIVE ESTIMATION OF ATTRIBUTE VALUES.

CATEGORY 3.

TENTATIVE DIAGNOSIS	PATIENT ASSESSMENT PROFILE	ASSIGNED SEVILL	COMPUTED SEVILL	DIFFERENCE
4	0 0 0 0 0 0 0 0 0 0 0 0	5*	23.95	-18.95
3	0 0 0 0 0 0 0 0 0 0 0 0	5	23.95	-18.95
3	0 0 0 1 0 0 0 0 0 0 0 0	10	25.81	-15.81
30	1 0 0 0 0 0 0 0 0 0 0 0	7	30.54	-23.54
5	1 0 0 0 0 0 0 0 0 0 0 0	7	30.54	-23.54
7	1 0 0 0 0 0 0 0 0 0 0 0	7	30.54	-23.54
8	1 0 0 0 0 0 0 0 0 0 0 0	7	30.54	-23.54
10	1 0 0 0 0 0 0 0 0 0 0 0	7	30.54	-23.54
8	0 0 0 0 0 0 1 0 0 0 0 0	20	49.70	-29.70
4	0 0 0 0 0 0 1 0 0 0 0 0	15	49.70	-34.70
3	0 0 0 0 0 0 1 0 0 0 0 0	15	49.70	-34.70
3	0 0 0 0 0 0 0 1 0 0 0 0	10	34.66	-24.66
5	1 0 0 1 0 0 0 0 0 0 0 0	10	31.95	-21.95
8	1 0 0 1 0 0 0 0 0 0 0 0	10	31.95	-21.95
6	0 0 0 1 0 0 1 0 0 0 0 0	15	55.75	-40.75
3	0 0 0 1 0 0 1 0 0 0 0 0	20*	55.75	-35.75
6	0 0 0 1 0 0 0 1 0 0 0 0	15	44.62	-29.62
8	1 0 0 0 0 0 0 1 0 0 0 0	30	39.36	-9.36
8	0 0 0 0 0 0 0 0 1 0 0 0	20	32.94	-12.94
8	0 0 0 0 0 0 0 0 1 0 0 0	30	32.94	-2.94
6	0 0 0 0 0 0 0 0 1 0 0 0	30*	32.94	-2.94
5	1 0 0 1 0 0 1 0 0 0 0 0	40	64.57	-24.57
6	1 0 0 1 0 0 1 0 0 0 0 0	40	64.57	-24.57
7	1 0 0 1 0 0 1 0 0 0 0 0	40*	64.57	-24.57
8	1 0 0 1 0 0 0 1 0 0 0 0	40	49.45	-9.45
8	0 0 0 1 0 0 0 1 0 0 0 1	60	82.38	-22.38
7	0 0 0 1 0 0 1 1 0 0 0 0	40	82.13	-42.13
6	1 0 0 1 0 0 0 0 0 0 1 0	40	56.70	-16.70
6	1 0 0 0 0 0 0 0 1 0 0 0	25	40.40	-15.40
6	1 0 0 0 0 0 1 1 0 0 0 0	30	65.77	-35.77
8	1 0 0 0 0 0 0 2 0 0 0 0	40	49.53	-9.53
8	1 0 0 1 0 0 1 0 0 0 0 1	60	84.55	-24.55
8	1 0 0 1 0 0 0 0 1 0 0 0	40	43.18	-3.18
6	1 0 0 1 0 0 0 0 1 0 0 0	50	43.18	6.82
31	1 0 0 1 0 0 1 0 0 0 1 0	75	115.37	-40.37
5	1 0 0 0 0 0 0 0 1 0 1 0	60	55.07	4.93
8	1 0 0 1 0 0 1 0 1 0 0 0	90	73.48	16.52
8	1 0 0 1 0 0 2 1 0 0 0 0	110*	113.89	-3.89
6	1 0 0 1 0 0 0 0 1 0 1 0	75	84.95	-9.95
8	1 0 0 1 0 0 0 0 1 0 1 0	90	84.95	5.05

TABLE 4.2 (CONTINUED)

CATEGORY 3. (CONTINUED)

TENTATIVE DIAGNOSIS	PATIENT ASSESSMENT PROFILE	ASSIGNED SEVILL	COMPUTED SEVILL	DIFFERENCE
6	1 0 0 1 0 0 1 1 0 0 1 0	125	143.11	-18.11
8	1 0 0 0 0 0 1 1 1 0 0 0	115*	74.01	40.99
6	1 0 0 0 0 0 1 0 1 0 1 0	110*	88.52	21.48
7	1 0 0 1 0 0 2 2 0 0 0 0	150*	135.20	14.80
5	1 0 0 1 0 2 0 0 0 0 0 0	150	77.52	72.48
6	0 0 0 1 0 0 1 1 1 0 1 0	125	130.87	-5.87
6	1 0 0 1 1 0 0 0 1 0 1 0	115	154.68	-39.68
1	0 0 0 0 0 3 0 0 0 0 0 0	160	88.97	71.03
1	0 0 0 0 0 3 1 0 0 0 0 0	175	146.18	28.82
1	0 0 0 0 0 3 0 0 0 0 1 0	175	121.58	53.42
1	0 0 0 1 0 3 1 0 0 0 0 0	190	185.22	4.78
1	0 0 0 1 0 3 0 1 0 0 0 0	190*	165.86	24.14
2	0 0 0 1 0 3 0 0 0 0 1 0	190	179.60	10.40
6	1 0 0 1 0 0 1 1 0 0 3 1	250*	232.94	17.06
1	0 0 0 1 1 3 0 0 0 0 0 0	225	181.44	43.56
8	1 0 0 1 0 0 2 2 1 0 1 0	200	205.65	-5.65
2	0 0 0 1 0 3 1 1 0 0 0 0	225	186.95	38.05
30	1 0 0 1 0 3 0 0 0 0 1 0	225	200.22	24.78
1	0 0 0 1 1 3 1 0 0 0 0 0	230	217.55	12.45
2	1 0 0 0 0 3 1 0 0 0 1 0	235*	204.73	30.27
2	0 0 0 1 0 3 1 0 1 0 0 0	205	222.86	-17.86
2	0 0 0 1 0 3 2 1 0 0 0 0	225	180.98	44.02
5	2 0 0 1 0 0 2 2 0 0 3 0	300*	275.36	24.64
1	1 0 0 0 0 3 0 0 1 0 1 0	235	250.88	-15.88
2	0 0 0 1 1 3 0 1 1 0 0 0	250*	236.79	13.21
30	1 0 0 1 0 3 1 1 0 0 1 1	310	245.05	64.95
1	0 0 0 1 2 3 0 1 0 0 1 0	300	233.66	66.34
30	0 0 0 1 1 3 1 2 1 0 1 0	375*	345.86	29.14
8	2 0 0 1 0 2 2 1 2 0 1 0	400*	336.66	63.34
30	1 0 0 1 1 3 0 2 1 0 1 1	400	450.17	-50.17
30	1 0 0 1 2 3 0 2 1 1 1 1	500*	488.96	11.04

RMS ERROR: 30.31

* INDICATES A TRAINING SET PATTERN

TABLE 5.1

SYSTEM SPECIFICATION OF CCD CAMERA
COMPUTER VIDEO SYSTEM

Overall System Specifications

Solid state CCD TV camera sensitive to light levels from 10 to 1000 foot-candles (visible spectrum.)

CCD image sensor array consisting of 100x100 elements (pixels).

Video data rate of 30 frames/second synchronized to standard video systems.

Camera-to-computer distance of up to 500 feet.

Standard TV monitor display of input scene.

Computer control of camera pan, tilt, zoom, focus, iris for automated tracking.

Computer controlled picture digitization.

Digitization of each picture element to *16 gray levels*.

2500 words of 16 bit memory to hold one picture.

16K dual port semiconductor buffer memory for video data.

Standard TV monitor display of scene in buffer memory.

Random or sequential memory access by host computer.

Capability to load buffer memory from computer to display computer generated scenes.

CAMAC computer interface.

Major Components

CCD image sensor camera.

Camera lens, pan, and tilt servos.

Level Shifters required for CCD operation.

Major Components (cont'd)

Television monitors.

Analog-to-digital converter.

Digital memory.

Digital-to-analog converter.

CAMAC interface.

CCD Image Sensor Camera Specifications

100% dynamic range capability for light levels from 10 to 1000 foot-candles of reflected illumination (visible spectrum).

100x100 array of image sensitive elements.

Flexible operating rate to allow for synchronization to standard video system scan rates.

16 gray level accuracy between input illumination and corresponding output voltage.

Minimum of 15 db signa/noise ratio, analog video signa/digital shifting coupling noise.

Maximum of 5% output nonlinearity between cells.

Maximum of 100 millivolts of dark noise @ 20°C.

Zoom Lens Specifications

Operational

Zoom Speed:	4 to 20 seconds
Focus Speed:	8 to 35 seconds
Iris Speed:	2 to 5 seconds

Electrical

Input voltage: 12VDC (maximum)

Normal Operating
Current at 8V : 60 ma Running
150 ma at stop (with clutch slipping)

Zoom Lens Specifications (cont'd)

Optical

Focal Length Range:	15-150mm
Relative Aperture :	f:2.5
Maximum Coverage Diameter :	15.9mm
Field Angles :	12.5 to 2.5 degrees
Lens Mount :	'C' (removable)

Pan-Tilt Drive Specifications

Operational

Angular Travel:	Pan: 0 to 350 degrees
	Tilt: $\pm$ 90 degrees
Speed :	Pan: 9 degrees/sec
	Tilt: 4 degrees/sec

Electrical

Voltage :	24 VAC
Power :	Pan 10VA
	Tilt 45VA
Normal Operating: Current	Pan: .4 Amp
	Tilt: 1.8 Amp

TABLE 5.2

SYSTEM SPECIFICATIONS FOR FULL RESOLUTION COMPUTER VIDEO INTERFACE USING VIDICON CAMERA, MAGNETIC DISC, ANALOG RECORDING AND TIME BASE EXPANSION AND COMPRESSION

Input Signal

Compatibility

US Television Std	EIA-RS-180A
No. of lines/frame	525
No. of fields/frame	2, interlaced
Field rate	59.94 Hz
Line rate	15734 KHz
Field time	16.6834 msec
Line time	63.5566 μsec
Signal amplitude (nom.)	1.0Vpp composite

Frame Memory

Storage media	6.5" video disc
Rotation speed	3596.40 rpm
Disc control	servocontrolled
Disc jitter (time base stability)	< 500 nsec/rev
Video heads	flying - 1 TV field/track
Headsdown rpm	∿ 3000 rpm
Head/disc velocity	1000-1150 i.p.s.
Head flying height	8-12 μin.
Head gap	40-50 μin.
Track width	0.015 in.
Max. no of tracks/in.	40
Storage method	Wideband FM Blanking @ 5.5mHz Peak wht. @ 7.5 mHz
Recording method	Saturated
Recording sequence	1 frame erase 1 frame write
Recording lockout time	66.733 msec
E-E availability	During record mode only
Input/output impedance	75Ω$\pm$ 5%, dc-5 mHz
Input/output signal levels	1.0 Vpp composite, nominal
S/Hum ratio	> 40 db $\frac{pp}{pp}$

Frame Memory (cont'd)

S/N ratio	> 45 db $\frac{pp}{rms}$ (unweighted)
Freq response	dc-3.0 mHz $\pm$ 1db dc-4.2 mHz $\pm$ 3db
Tilt	∿ 2%
"K"-factor	∿ 3%
Time base stability	< $\pm$ 250 nsec, peak/field

Timebase Compandor Signal Processing

Technology	Digital processing
Input compatibility	10. Vpp analog comp video
Outputs available	1.0 Vpp analog LF video 8-bit digital video, 34.0908K samples/sec
No. of lines addressed per field frame	240/480
No. of samples/line	512
Sample interval	97.778 nsec
Sampled active line time	50,062 μsec
Line access	Sequential or random
Line throughput time	19.067 ms for 512 8-bit words
A/D,D/A resolution	8-bit
High speed A/D converter clock	10.22725 MHz
Timebase jitter correction method	Parallel digital data track
Data encoded	Composite sync
Encode method	Bi-phase, M
Encode rate	4.09090 MHz
Datastream clock recovery method	PLL
Recovered reference freq.	2.04545 MHz
Fast 2 line buffer memory	MOS shift register
Capacity	1024x8 bits
Write clock - from Hi speed A/D	10.22725 MHz
Read clock - to RAM	1.022725 MHz
Slow 2 line buffer memory	MOS RAM
Capacity	1024x8 bits
Write clock - from shift register	1.022725 MHz
Read clock - to D/A converter	34.0908 KHz

TABLE 6.1 DEMONSTRATION OF SUCCESSFUL TRACKING OF LOCATION OF DARK OBJECT

OBJECT AT POSITION 1 (See Figure 6.1 for illustration)

Coarse Position estimate at	(-5,19)
After adjustment, fine estimate at	(-1,7)
After adjustment, coarse estimate at	(0,0)
fine estimate at	(0,7)
After adjustment both estimates return (0,0) - Object is centered.	

OBJECT AT POSITION 2

Coarse Position estimate at	(-2,20)
After adjustment, fine estimate at	(4,7)
After adjustment, coarse estimate at	(0,0)
Fine position estimate at	(-2,7)
After adjustment both estimates return (0,0) - object is centered.	

OBJECT AT POSITION 3

Coarse Position estimate at	(23,-23)
After adjustment fine estimate at	(-1, 7)
After adjustment both estimates return (0,0) - object is centered.	

OBJECT AT POSITION 4

Coarse position estimate at	(-23,-23)
After adjustment fine estimate at	(- 7, -7)
After adjustement, coarse estimate at	(0, 0)
fine estimate at	(1, 0)
After adjustment both estimates return (0,0) - object is centered.	

OBJECT AT POSITION 5

Coarse position estimate at	(-23,23)
After adjustment, fine estimate at	(-4, -6)
After adjustment, both estimates return (0,0) - object is centered.	

TABLE 6.1 (Cont'd)

OBJECT AT POSITION 6

Coarse position estimate at	(-2,0)
After adjustemtne, fine estimate at	(7,7)
After adjustment, coarse estimate at	(-2,-2)
After adjustment, fine estimate at	(6,7)
After adjustment, coarse estimate at	(0,0)
fine estimate at	(0,5)
After adjustment, both estimates return (0,0) - object is centered.	

OBJECT AT POSITION 7

Coarse position estimate at	(-17,-23)
After adjustment, fine estimate at	(0, 0)
coarse estimate at	(23, -23)
After adjustment, fine estimate at	(0, 7)
After adjustment both estimates return (0,0) - object is centered.	

TABLE 6.2 DEMONSTRATION OF SUCCESSFUL RECOGNITION OF TANKS REGARDLESS OF ORIENTATION

# of Pattern Presented	Recognized as Pattern # 1	2	3	4	5	6	7	8	9	10	11	12
1	1124	852	1000	788	808	832	1068	884	816	752	764	884
2	872	1128	1020	800	684	764	1016	872	924	668	720	792
3	692	900	1168	828	736	624	932	788	1072	544	684	692
4	844	748	784	1156	976	864	780	892	680	1064	844	756
5	712	744	868	896	1276	892	656	800	596	1020	928	832
6	728	880	668	704	988	1204	632	752	476	892	944	968
7	984	888	932	848	684	748	1248	880	876	708	632	728
8	688	760	900	864	692	564	1000	1032	764	508	712	704
9	572	852	1072	948	784	712	1004	740	1264	704	692	700
10	772	644	672	876	1008	832	564	740	680	1288	1012	780
11	780	724	744	868	976	904	580	812	600	1008	1220	820
12	772	780	640	628	920	1016	532	804	536	912	972	1068

Numbers exhibited are coefficients of correlation yielded by Associative Memory. Correct recognition is demonstrated by diagonal elements of array being the largest in any row.

References

1. Yoh-Han Pao and F. L. Merat "Distributed Associative Memories for Patterns", IEEE Transactions on Systems, Man and Cybernetics, p. 620, November 1975.

2. Yoh-Han Pao and J. L. Altman "Associative Mrmories As Multipath Logic Switches" presented at 1975 International Symposium on Multi-Valued Logic. Published in Proceedings of Symposium.